Amendments to the Specification:

Please replace paragraph [0040] with the following amended paragraph:

[0040] Data extracted using the module 300 is then processed by a data-mapping module 301. Operations of the data-mapping module 301 may include selecting a virtual event category to which an event at issue resembles and obtaining initial forecast information, such as [[forecast]] fractional build curve, forecast, and remaining data forecast, based on information obtained by the data extraction module 300. Operations of the data-mapping module 301 are described below in more detail.

Please replace paragraph [0052] with the following amended paragraph:

[0052] Table 1 below provides a list of variables used by the forecast engine of FIG. 4 in forecasting. One of ordinary skill in the art will appreciate that variables listed in Table 1 are provided as an example and the present invention can be implemented using various combinations of variables in Table 1 or additional variables, without departing from the scope of the invention. As such, modifications and substitutions by one of ordinary skill in the art are considered to be within the scope of the present invention.

ID	Description
FWN	Forecast Window Number; identifies the time span in the future for calculation of forecasts
HWN	Historical Window Number; identifies the time span in historical data that will be used to generate forecasts
FA	Maximum number of units (weeks) that will be used in historical rolling averages
[[UF]]	**[[Unconstraining Factor]]**
TC	Timing Category
R	Resource

$Bbkngs_{e,r,dc}$	Net bookings at the event, resource, discount category level
$IDC_{tc,r}$	Ideal set of discount categories at the timing category resource level; To be used to calculate discount category statistics
EH	Set of all historical events
EF	Set of all future events
EC	Set of all completed events in the current season which have not yet gone through the daily update process; Once used to update statistics, an event becomes a member of EH.
Fs	Flexibility status of price discount category. If true, then the optimization can change the availability status, if false, the optimization cannot change the status.
$Dsc\_ct\_stat_{tc,r}$	Discount category stats at the timing category resource level
EID	Each epoch date is assigned a sequential ID to be used as a reference in the database.
ESD	The fractional build curve consists of a series of epoch start dates, representing the days prior to a specified event.
Dys_Prior	The number of days prior to a specified event
$Frc\_Bld_{tc,r}$	Fractional build curve at the timing category resource level
α	Historical smoothing constant used during initialization to determine weights for rolling averages
$\omega_{\alpha j}$	The normalized weight for the historical observation that is $\|j\|$ FWN units away from the target FWN
β	Daily update smoothing constant used during the daily update process to incorporate data from just completed events into statistics
ω_{β}	The normalized weight to incorporate new

	data in the daily update process
$Fnl\_Fcst_{tc,r}$	Final unconstrained remaining demand forecast at the event, resource, discount category level
$Fcst\_Rem\_Dmd_{e,r,dc}$	Net unconstrained remaining demand forecast at the event, resource, discount category level
Post Date	**a defined date subsequent to a specified event**

Table 1

Please replace paragraph [0062] with the following amended paragraph:

[0062] The data pooler may calculate initial fractional build curve statistics at the FWN–TC–resource level. To calculate initial fractional build curve statistics, fractional build curves may be generated for each future combination of FWN–TC–resource specified in the future data. They may be generated from unconstrained historical data in the same TC and with HWN equal to the FWN of the event and plus/minus half the FA. The weeks at the beginning and end of the season may use what is available of the FA. For instance, the first week may use historical weeks 1–3, and the last week may use the last three historical weeks. Next, for each epoch id, total net bookings that have occurred thus far may be cumulated for all events in the same HWN–TC–resource.

$$bkngs_{eid(i),hwn,tc,r} = \sum_{dp \geq dpeid(i)} bkngs_{eh,hwn,tc,r,dp}, \qquad (7)$$

$$\forall\, tc \in TC,\ r \in R,\ hwn \in HWN,\ eid \in EID$$

Then for each HWN–TC–resource, total net bookings may be determined as follows:

$$bkngs_{hwn,tc,r} = bkngs_{eid(0),hwn,tc,r}, \forall\, tc \in TC,\ r \in R, hwn \in HWN \qquad (8)$$

A fractional build may be calculated by dividing the cumulative value at each break point by the total.

$$frac\_bld_{eid(i),hwn,tc,r} = \frac{bkngs_{eid(i),hwn,tc,r}}{bkngs_{hwn,tc,r}},$$
$$\forall\ tc \in TC,\ r \in R, hwn \in HWN, eid \in EID \qquad (9)$$

Subsequently, a fractional build curve for future FWN–TC may be calculated by taking a weighted average of the historical curves from the applicable HWN–TC. The weights may be calculated by normalizing the values found by the following equation: {a x (1-a) (|j|-1)}, where a is a stored smoothing constant and j is the number of weeks off the target week in question. A different weight may be assigned to a HWN for each FWN it is used in. Specifically, equations (10)–(12) may be used to calculate a fractional build curve

$$j_{fwn,hwn} = (fwn - hwn)\begin{cases} j_{\max} = truncate\left(\frac{FA}{2}\right) \\ j_{\min} = [[\_\text{truncate}\left(\frac{FA}{2}\right)]]\ \underline{(-1) * truncate\left(\frac{FA}{2}\right)} \end{cases} \qquad (10)$$

$$\varpi_{j\,fwn,hwn^{tc,r}} = \frac{\left(a \times (1-a)\right)^{\left(|j_{fwn,hwn}|-1\right)}}{\sum_{j\min}^{j\max}\left(a \times (1-a)^{\left(|j_{fwn,hwn}|-1\right)}\right)},$$
$$\forall\ j, tc \in TC, r \in R \qquad (11)$$

$$frac\_bld_{eid(i),fwn,tc,r} = \sum_{hwn}\left(\omega_{j_{fwn,hwn}^{tc,r}} \times frac\_bld_{eid(i),hwn,tc,r}\right) \qquad (12)$$

$$\forall\ tc \in TC,\ r \in R,\ fwn \in FWN,\ eid \in EID$$

Finally, these values may be stored as the fractional build curve statistics.

Please replace paragraph [0063] with the following amended paragraph:

[0063] The data pooler may be used to determine initial final net forecast at the FWN–TC–resource level. First, the data pooler may calculate the average unconstrained net demand for all historical events in each HWN–TC **resource** by dividing the total net bookings from all events in a given HWN by the number of events as described in Equation (13).

$$avg - bkgs_{hwn,tc,r} = \frac{bkngs_{hwn,tc,r}}{\left[\left[\sum_{eh \in hwn} i_{eh} = 1\right]\right] \underline{\sum_{eh \in hwn} i_{eh}}}, \quad (13)$$
$$\forall \; tc \in TC, r \in R, hwn \in HWN$$

Second, the final net forecast for each future FWN–TC **resource** may be calculated by taking a weighted average of the historical averages from the applicable FWN – TC **resource**. The weights may be calculated by normalizing the values found by the following equation: $\left\{\alpha \times (1-\alpha)^{(|j|-1)}\right\}$ where α is a stored smoothing constant and j is the number of weeks off the target week in question. A different weight may be assigned to a HWN for each FWN it is used in.

$$j_{fwn,hwn} = (fwn - hwn)\begin{cases} j_{\max} = truncate\left(\frac{FA}{2}\right) \\ j_{\min} = \left[\left[\_truncate\left(\frac{FA}{2}\right)\right]\right] \underline{(-1) * truncate\left(\frac{FA}{2}\right)} \end{cases} \quad (14)$$

$$\varpi_{j_{fwn,hwn},tc,r} = \frac{\left(a \times (1-a)^{(|j_{fwn,hwn}|-1)}\right)}{\sum_{j\min}^{j\max}\left(a \times (1-a)^{(|j_{fwn,hwn}|-1)}\right)},$$
$$\forall \; j, tc \in TC, r \in R \quad (15)$$

$$fnl\_fcst_{fwn,tc,r} = \sum_{hwn}\left(\omega_{j_{fwn,hwn},tc,r} \times bkngs_{hwn,tc,r}\right), \quad (16)$$
$$\forall \; tc \in TC, \; r \in R, fwn \in FWN$$

Third, the data pooler may store back the values as the final net forecast.

Please replace paragraph [0064] with the following amended paragraph:

[[0064]] The data pooler may calculate final net forecast by flexibility status at the [[FWN–TIC–resource–flexibility]] **FWN–TC–resource–flexibility** status level. First, the final net forecast may be split by flexibility status. This may be done for the booking curve. Second, the price discount category statistics for the non-flexible price discount categories may be added.

$$flex\_cat\_stat_{tc,r,fst} = \sum_{fs="true"} dsc\_ct\_stat_{tc,r,dc,fs}$$
$$\forall tc \in TC, r \in R \quad (17)$$

Third, the final net forecast at the timing category–resource–flexibility status level may be calculated by multiplying the final net forecast by the fraction flexible and 1 minus the fraction flexible as shown in Equations (18) and (19).

$$fnl\_fcst_{fwn,tc,r,fs_t} = \left(flex\_cat\_stat_{tc,r,fs_t} \times fnl\_fcst_{fwn,tc,r}\right) \quad \forall\ tc \in TC,\ r \in R, fwn \in FWN \tag{18}$$

$$fnl\_fcst_{fwn,tc,r,fs_t} = \left(\left(1 - flex\_cat\_stat_{tc,r,fs_t}\right) \times fnl\_fcst_{fwn,tc,r}\right), \quad \forall tc \in TC, r \in R,\ fwn \in FWN \tag{19}$$

Please replace paragraph [0065] with the following amended paragraph:

[[0065]] The data pooler may calculate initial net remaining demand forecast at the [[FWN–TIC–resource]] <u>**FWN–TC–resource**</u> level. Specifically, it may apply the price category decomposition statistics to the final net forecast as follows.

$$fnl\_fcst_{fwn,tc,r,dc} = fnl\_fcst_{fwn,tc,r} \times dsc\_ct\_stat_{tc,r,dc} \quad \forall tc \in TC, r \in R,\ fwn \in FWN,\ dc \in IDC_{tc,r} \tag{20}$$

In so doing, the data pooler may perform the following calculations at the event–resource–discount category level. First, it may determine the number of days prior using Equation (21).

$$dys\_prior_{ef} = \left(event\_date_{ef} - \left(post\_date + 1\right)\right), \forall\ ef \in EF \tag{21}$$

Second, it may determine the last epoch ID passed by each future event.

$$\left\| eid(ef) \ni dys\_prior_{eid(l-1)} \leq dys\_prior_{eid(ef)} < dys\_prior_{eid(i)} \right\|$$
$$\underline{eid(ef) \ni dys\_prior_{eid(i-1)} \leq dys\_prior_{eid(ef)} < dys\_prior_{eid(i)}} \tag{22}$$

Third, it may determine the remaining fraction to book for each future event by interpolating the fractional build curve between the days-left value and the event's epoch ID as shown in Equation (23).

$$\begin{aligned}
& frac_bld_{dp_{ef},r} = \\
& frac_bld_{eid(ef),fwn,tc,r} - \left(\frac{frac_bld_{eid(ef),fwn,tc,r} - frac_bld_{eid(ef+1),fwn,tc,r}}{dys_prior_{eid(ef),fwn,tc,r} - dys_prior_{eid(ef+1),fwn,tc,r}} \right) \\
& \text{x} \left(dys_prior_{eid(ef),fwn,tc,r} - dys_prior_{ef,r} \right) \\
& \forall\ eid \in EID, fwn \in TC,\ r \in R
\end{aligned} \tag{23}$$

Fourth, it may multiply the stored final net forecast by (1–booking fraction).

$$\begin{aligned}
& fcst_rem_dmd_{ef,r} = \left(1 - frac_bld_{dp_{ef},r}\right) \text{x}\ fnl_fcst_{fwn,tc,r,dc} \\
& \forall\ ef \in EF,\ r \in R
\end{aligned} \tag{24}$$

Fifth, it may store back the calculated value as the remaining demand forecast.

Please replace paragraph [0073] with the following amended paragraph:

[0073] The second step in calculating the initial booking pace curve may include using $DP_{ef,}$ the number of days prior for each future event, that was calculated for the remaining demand. Third, *eid(ef),* the epoch ID for each future event, which was calculated for the remaining demand, may also be used. Fourth, for each epoch ID, the incremental difference in the fractional build curve associated with the future events are determined using Equation (25).

$$\begin{aligned}
& \Delta frac_bld_{eid(i),fwn,tc,r} = \left(frac_bld_{eid(i-1),fwn,tc,r} - frac_bld_{eid(i),fwn,tc,r} \right), \\
& \forall\ tc \in TC,\ r \in R,\ fwn \in FWN,\ eid \in EID
\end{aligned} \tag{25}$$

Fifth, the incremental difference in the fractional build curve between the current days prior and the event's epoch ID may be determined by subtracting fractional build percent found in the remaining demand calculations from the fractional build percent at the event's epoch ID.

$$\begin{aligned}
& [[\ \Delta frac_bld_{eid(ef),r} = \left(frac_bid_{eid(ef),r} - frac_bld_{dp,ef,r} \right), \\
& \forall\ r \in R,\ ef \in EF\ ]] \\
& \underline{\Delta frac_bld_{eid(ef),r} = \left(frac_bld_{eid(ef),r} - frac_bld_{dp,ef,r} \right),} \\
& \underline{\forall\ r \in R,\ ef \in EF}
\end{aligned} \tag{26}$$

Sixth, for each epoch ID greater than or equal to the future event's epoch ID, incremental net

bookings of each future event at the resource–flexible status level may be cumulated.

$$inc\_bkngs_{eid(i),ef,r,fs} = \sum_{dp<dp_{eid(i+1)}}^{dp \geq dp_{eid(i)}} bkngs_{ef,r,dp,fs}, \quad \forall ef \in EF, r \in R, eid \in \left(EID \geq eid(ef)\right), fs \in \{true, false\} \tag{27}$$

Seventh, for each epoch ID less than the future event's epoch ID, the forecasted incremental bookings may be determined by multiplying the final forecast by the incremental fractional build as shown in Equations (28) and (29). The resulting value may now be the bookings associated with the future epoch IDs.

$$inc\_fcst_{eid(i),fwn,tc,r,fs} = \Delta frac\_bld_{eid(i),fwn,tc,r} \times fnl\_fcst_{fwn,tc,r,fs}, \quad \forall eid \in EID,\ fwn \in FWN,\ tc \in TC,\ r \in R,\ fs \in \{true, false\} \tag{28}$$

$$inc\_bkngs_{eid(i),fwn,tc,r,fs} = inc\_fcst_{eid(i),fwn,tc,r,fs}, \quad \forall eid \in EID,\ fwn \in FWN,\ tc \in TC,\ r \in R,\ fs \in \{true, false\} \tag{29}$$

Eighth, for the future event's epoch ID, the incremental forecast for that epoch ID may be determined by multiplying the final forecast associated with the event by the incremental fractional build for the epoch ID.

$$inc\_fcst_{eid(ef),r,fs} = \Delta frac\_bld_{eid(ef),r} \times fnl\_fcst_{fwn,tc,r,fs}, \quad \forall\ ef \in EF,\ r \in R,\ fs \in \{true, false\} \tag{30}$$

Ninth, for each future event, the incremental forecast for the event's epoch ID to the net bookings previously accrued in the event's epoch ID may be added. If epoch IDs are incremented daily, previous accrual may set to 0.

$$inc\_bkngs_{eid(ef),r,fs} = inc\_bkngs_{eid(ef),r,fs} + inc\_fcst_{eid(ef),r,fs}, \quad \forall ef \in EF,\ r \in R,\ fs \in \{true, false\} \tag{31}$$

Tenth, to calculate graphing values for booking curve for a future event, the incremental bookings from each epoch ID may be cumulated up to the next epoch ID.

$$book\_curve_{eid(i),ef,r,fs} = \sum_{j=\max(eid)}^{eid(i)} inc\_bkngs_{eid(j),ef,r,fs},$$
$$\forall eid \in EID,\ ef \in EF,\ r \in R,\ fs \in \{true, false\} \tag{32}$$

Finally, the booking curve statistics may be stored.

Please replace paragraph [0072] with the following amended paragraph:

[0072] Final net forecast may be updated for the completed events at the FWN–TC–resource level as follows. First, the average unconstrained net demand for all completed events in each FWN–TC level may be calculated by summing the bookings from all completed events in that FW and dividing by the number of events.

$$avg\_bkngs_{fwn_{ec},tc,r} = \frac{bkngs_{fwn_{ec},tc,r}}{\left[\left[\sum_{ec \in fwn} i_{ec} = 1\right]\right] \sum_{ec \in fwn} i_{ec}},$$
$$\forall\ tc \in TC,\ r \in R,\ fwn \in fWN \tag{42}$$

Second, the new forecast input may be set to the average bookings just calculated.

$$fnl\_fcst_{fwn_{ec},tc,r} = avg\_bkngs_{fwn_{ec},tc,r},$$
$$\forall\ tc \in TC,\ r \in R,\ fwn \in fWN \tag{43}$$

Third, the stored final net forecast for applicable FWN–TC–resource level may be calculated as follows: (1) multiplying the completed event's final net forecast by the stored smoothing constant for daily updates; (2) multiplying the stored final net forecast by 1 minus the stored constant for daily updates; (3) adding the two together using Equation (44); and (4) storing back the calculated values as the new final net forecast.

$$fnl\_fcst\_store_{fwn,tc,r}$$
$$= \left(fnl\_fcst\_new_{fwn_{ec},tr,r} \mathrm{x} \varpi_{\beta}\right) + \left(fnl\_fcst\_old_{fwn,tc,r} \mathrm{x} \left(1 - \varpi_{\beta}\right)\right),$$
$$\forall\ tc \in TC,\ r \in R,\ fwn \in FWN$$

Please replace paragraph [0076] with the following amended paragraph:

[0076] Third, an optimization module may be applied to each row k of the matrix. For example, an optimization module may perform the following six steps:

a) Send forecast of net remaining demand for each event–resource–price discount category with the availability status of the row, to the optimization module. This may be referred to as "forecast mean" or $fcst\_rem\_dmd_{k,ef,r,dc_{as}}$

b) Set variance of forecast mean, which may be referred to as "forecast variance" to the mean as follows:

$$var\_rem\_dmd_{k,ef,r,dc_{as}} = fcst\_rem\_dmd_{k,ef,r,dc_{as}} \tag{45}$$

c) Aggregate the forecast mean for all discount categories with availability status open

$$agg\_fcst_{k,ef,r} = \sum_{dc_{as}=open} fcst\_rem\_dmd_{ef,r,dc_{as}} \tag{46}$$

d) Aggregate the forecast variance for all discount categories with availability status open

$$agg\_\mathrm{var}_{k,ef,r} = \sum_{dc_{as}=open} \mathrm{var}\_rem\_dmd_{k,ef,r,dc_{as}} \tag{47}$$

e) Calculate the average profit per seat using configuration for row k by aggregating the profit per discount category times the forecast mean for the discount category and dividing by the aggregated resource mean

$$agg\_profit_{k,ef,r} = \sum_{dc_{as}=open} \left(fcst\_rem\_dmd_{k,ef,r,dc_{as}} \times profit_{ef,r,dc}\right) \tag{48}$$

$$avg\_profit_{k,ef,r} = \frac{agg\_profit_{k,ef,r}}{agg\_fcst_{k,ef,r}} \tag{49}$$

f) The standard deviation equals the square root of the variance, which may be used in terms of the aggregate value

$$agg\_st\_dev_{k,ef,r} = \sqrt{agg\_\mathrm{var}_{k,ef,r}} \tag{50}$$

g) The first check is to determine if the aggregate forecast for row k is significantly less than the remaining capacity for the resource. This check may be performed by adding four times the standard deviation to the forecast mean and comparing it

to the remaining capacity of the resource less 1 (to adjust for rounding error)

$$\max\_dmd_{k,ef,r} = \left(agg\_fcst_{k,ef,r} + \left(4 \times agg\_st\_dev_{k,ef,r}\right)\right) \tag{51}$$

$$undersell = \left\{true\ if \left(rem\_cap_{ef,r} - 1\right) \geq \left(\max\_dmd_{k,ef,r}\right)\right\} \tag{52}$$

h) If *undersell* equals true, the expected demand equals the aggregate mean, the expected profit equals the average profit per seat times the aggregate mean, and the marginal value of a single seat equals the average profit per seat.

$$\exp\_dmnd_{k,ef,r} = agg\_fcst_{k,ef,r} \tag{53}$$

$$\begin{gathered} [[\exp\_dmnd_{k,ef,r} = agg\_fcst_{k,ef,r} \times avg\_profit_{k,ef,r}]] \\ \underline{\exp\_profit_{k,ef,r} = agg\_fcst_{k,ef,r} \times avg\_profit_{k,ef,r}} \end{gathered} \tag{54}$$

$$m\arg\_value_{k,ef,r} = avg\_profit_{k,ef,r} \tag{55}$$

i) If *undersell* equals false, the next check is to determine if a *sellout* situation exists; the aggregate forecast for row k is significantly greater than the remaining capacity for the resource. This check may be performed by subtracting four times the standard deviation to the forecast mean and comparing it to the remaining capacity of the resource less 1 (to adjust for rounding error)

$$\min\_dmd_{k,ef,r} = \left(agg\_fcst_{k,ef,r} - \left(4 \times agg\_st\_dev_{k,ef,r}\right)\right) \tag{56}$$

$$sellout = \left\{true\ if \left(rem\_cap_{ef,r} - 1\right) \leq \left(\min\_dmd_{k,ef,r}\right)\right\} \tag{57}$$

j) If *sellout* equals true, the expected demand equals the remaining capacity, the expected profit equals the average profit per seat times the remaining capacity of the resource, and the marginal value of a single seat equals the average profit per seat.

$$[[\exp\_dmnd_{k,ef,r=}rem\_cap_{ef,r}]]\ \underline{\exp\_dmnd_{k,ef,r} = rem\_cap_{ef,r}} \tag{58}$$

$$\begin{gathered} [[\exp\_profit_{k,ef,r=}rem\_cap_{ef,r} \times avg\_profit_{k,ef,r}]] \\ \underline{\exp\_profit_{k,ef,r} = rem\_cap_{ef,r} \times avg\_profit_{k,ef,r}} \end{gathered} \tag{59}$$

$$m\arg\_value_{k,ef,r} = avg\_profit_{k,ef,r} \tag{60}$$

k) If *undersell* and *sellout* both equal false, the expected demand, profit, marginal value are calculated by determining the area under the curve generated by the probability mass function (*pmf*) of the normal distribution clipped to a minimum value of 0 and a maximum value of remaining capacity, with the mean equaling

the aggregate forecast mean and the standard deviation equaling the aggregate standard deviation.

$$\exp\_dmnd_{k,ef,r} = \sum_{x=\max(0,\min\_dmd_{k,ef,r})}^{rem\_cap_{ef,r}} \left(X \times pmf_N\left(x, agg\_fcst_{k,ef,r}, agg\_st\_dev_{k,ef,r}\right)\right) \tag{61}$$

$$\exp\_profit_{k,ef,r} = \sum_{x=\max(0,\min\_dmd_{k,ef,r})}^{rem\_cap_{ef,r}} \left(avg\_profit_{k,ef,r} \times \left(x \times pmf_N\left(x, agg\_fcst_{k,ef,r}, agg\_st\_dev_{k,ef,r}\right)\right)\right) \tag{62}$$

$$m\arg\_value_{k,ef,r} = \frac{\exp\_profit_{k,ef,r}}{\exp\_dmnd_{k,ef,r}} \tag{63}$$